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An Analysis of Capacity Adjustment and Uncertainty in the Petroleum Refining Industry

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Abstract

This paper investigates the effect of uncertainty on the investment decisions of petroleum refineries in the US. We construct uncertainty measures from commodity futures market and use data on actual capacity changes to measure investment episodes. Capacity changes in US refineries occur infrequently and a small number of investment spikes account for a large fraction of the change in industry capacity. Given the lumpy nature of investment adjustment in this industry, we empirically model the investment process using hazard models. An increase in uncertainty measures decreases the probability a refinery adjusts its capacity. The results are robust to various investment thresholds and uncertainty measures used in the analysis. Our findings lend support to theories emphasizing the role of irreversibility in investment decisions.

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I. Introduction

Dixit and Pindyck (1994) develop a theory of investment that focuses on the irreversibility inherent in many capital projects and the effect of uncertainty on the timing of these types of irreversible investment projects. In their model, uncertainty in the future profitability of an investment that is irreversible, or partially irreversible, may cause a firm to delay an investment project in order to obtain additional information on the profitability of the investment. Dixit and Pindyck refer to this as "option value of waiting to invest" and firms consider this "option" when making investment decisions.[2] In this paper, we test this main prediction of their model by examining how the timing of capital projects responds to changes in the volatility of input and output prices.[3]

The paper examines capital expansion and contraction events at individual US oil refineries. We believe this is a good testing ground for the Dixit and Pindyck model for three reasons. First, investments that involve the capacity expansion of a refinery will include a significant fraction of sunk costs. The investment in capacity expansion in refineries is largely composed of structures that are usually engineered and integrated into an existing production facility. Once in place a refinery cannot easily divest itself of such a capacity expansion project without bearing significant costs. Thus, it is reasonable to believe that a significant fraction of such investments is irreversible. Second, firms in the industry change their capacity in discrete investment and disinvestment bursts. Episodes of high investment activity are interspersed with episodes of zero investment activity. This pattern in US refineries is similar (though more stark) to recent empirical papers documenting the micro-adjustment patterns of plants and firms (Cooper, Haltiwanger and Power (hereafter CHP, 1999), Doms and Dunne (1998), and Nilsen and Schiantarelli (2003)). This discrete nature of investment in this industry will allow us to look at

[2] An early discussion of nonconvex adjustment costs is provided in Rothschild (1971). Dixit and Pindyck (1994) emphasize the role of irreversibilities along with uncertainty in the investment process.
[3] For a complete survey on recent development in the investment under uncertainty literature, see Carruth et al. (2000). Abel (1983) offers develops an alternative modeling framework where greater uncertainty actually increases the likelihood a firm invests.

the timing of capital projects and thus we will be able to see if firms delay capital projects when uncertainty rises. Third, the industry has well developed commodity future markets for its main input, crude oil, and its main outputs, heating oil and gasoline. We use the volatility in the futures prices to proxy for uncertainty in the economic environment in which refiners must make investment decisions.

Our data include annual observations on refining capacities for almost all US refineries in existence over the period 1985-2003. We use year-to-year changes in capacities to measure when firms undertake capital projects. The data measure only investment and disinvestment episodes that affect capacity expansion or contraction. These capacity-based data omit maintenance-driven investment and non-capacity changing investments such as investment in pollution control equipment.[4] In the case of environmental investments which are important in this industry, the timing of these kinds of investment is likely to be quite unrelated to the firm's optimal capital adjustment problem discussed in the literature. By using physical capacity measures, we reduce these types of measurement problems in our data and improve our ability to measure the timing of capital projects.[5]

The first part of our empirical analysis documents capital adjustment patterns in the US petroleum refining industry. We find that capacity adjustments by refiners are very infrequent. Approximately three-quarters of the year-to-year changes in capacity are zero. This pattern of inactivity in the investment data is consistent with models of irreversibility, as well as models that stress the presence of fixed adjustment costs (CHP and Cooper and Haltiwanger (2006)). The second part of the empirical analysis explores the relationship between price uncertainty and capacity adjustment. We estimate hazard model of capacity adjustment to examine the effect of uncertainty on the probability a refinery adjusts its capacity. We find that increases in uncertainty

[4] Caballero (2000) emphasizes the importance of distinguishing between maintenance-driven and expansion-driven investments.
[5] Two other recent studies use capacity changes to measure investment in the literature, Bell and Campa (1997) and Goolsbee and Gross (2000).

delays capacity changes, especially capital expansion projects. Our results are robust to a variety of adjustment thresholds and uncertainty measures.

The remainder of this paper proceeds as follows. Section II describes some basic features of the refining industry and the data that we use in the paper. In section III we discuss our measures of uncertainty. Section IV provides a detailed statistical analysis and presents empirical findings. Section V summarizes and concludes.

II. Investment in the Refining Industry

Constructing the capital stocks of firms and the changes in the capital stocks often involves difficult measurement issues.[6] Typically, authors use accounting data on the current dollar value of purchased plant and equipment and apply aggregate depreciation rates and capital price indices to construct a constant-dollar firm-level capital stock. These standard approaches to capital measurement at the micro level contain a number of drawbacks. On the one hand, many required data items for the creation of producer-level capital stocks are often missing at the micro level. For example, information on the economic depreciation of assets and the price of investment goods are typically unavailable at the producer level. On the other hand, accounting data on new investment contain a mix of capital expenditures that includes expansion-driven spending, maintenance-driven spending and non-capacity enhancing investments such as pollution control and occupational safety equipment. In the latter case, these may be mandated investments due to regulatory requirements. These mandated investments and maintenance-driven investments are driven by forces distinct from the firm's decision to expand or contract its capacity to produce output. Accounting data rarely allow the researcher to discriminate among these alternative investment categories. Moreover, these accounting based data are influenced by tax code issues and usually represent a mix of historical and current dollar data series. Economists prefer measures of the capital stock that are tied more directly to the physical capital stock or to the flow

[6] See CEH (1995) and Goolsbee and Gross (2000) for a detailed discussion of measurement issues.

of services provided by the capital stock of the firm. In this paper, we reduce some of the accounting-related problems by studying changes in actual capacities in refineries.

We use the petroleum refinery capacity data from the "Petroleum Supply Annual" published by the Energy Information Administration (EIA), Department of Energy. Beginning in 1980, the EIA implemented a mandatory annual survey of refinery capacities except for the period of 1995-1998 during which the survey was done biennially. It surveys both crude oil processing (distillation) capacity and downstream capacities for all operable refineries located in the 50 U.S. states, Puerto Rico, the Virgin Islands, Guam and other U.S. possessions. To fill in the missing data in 1995 and 1997, we supplement the EIA data by a private survey of refining capacities in 1995 and 1997 from the *Oil & Gas Journal (OGJ)*.[7] Because our primary uncertainty measure is derived from commodity futures market and unleaded gasoline futures markets did not exist before December 1984, our time period of analysis runs from 1985 to 2003. The final data set contains 224 refineries with a total of 3314 refinery-year observations.

As our basic measure of capital, we focus on the crude processing capacity (atmospheric distillation capacity) of refineries located in the 50 U.S. states.[8] Refining capacity is measured in two ways -- as the barrels per stream day (B/SD) and as the barrels per calendar day (B/CD). The former is "the maximum number of barrels of input (mainly crude oil) that a distillation facility can process within a 24-hour period when running at full capacity under optimal crude and product slate conditions with no allowance for downtime." The latter is "the amount of input that a distillation facility can process under usual operating conditions and allows limitations in downstream capability and downtime due to scheduled maintenance, turnaround, and slowdowns" (EIA, 2000, p 165-166). Throughout the analysis, we use refining capacities expressed as barrels per stream day in this study because changes in stream day capacities require a physical change in the actual processing units.

[7] The OGJ data only reports capacities measured in calendar days. We multiply the EIA 1994 data by the percentage change in OGJ data to obtain the 1995 data, and similarly for 1997 data.
[8] Crude distillation is the first and necessary procedure in a continuous refining process.

To investigate the investment-uncertainty relationship, we focus on capacity changes at refineries. We define capacity expansions from year y to $y+1$ as our measure of investment and capacity reductions from year y to $y+1$ as measured disinvestment. Refiners can increase their capacities through conventional capital project (e.g. adding a catalytic cracking unit) and through debottlenecking investments which are smaller investments that increase refining capacities but do not alter the number of processing units (EIA Staff report, 1999). Debottlenecking is usually accomplished at the same time as maintenance and repair. The additional capacity gained through debottlenecking is usually termed "capacity creep." Capacity reductions typically result from the shutdown of either a refinery or a distillation unit in a multi-unit refinery. Given that the debottlenecking can be done at minimum costs, one might expect refineries to frequently adjust their capacities. However, as depicted below, this is not the case.

Figure 1 shows the aggregate of capacity additions and the industry-level investment for petroleum refining (SIC code 2911 and NAICS code 32411) from the Annual Survey of Manufacturers (ASM) over the sample period. To accommodate construction lags, the ASM data is lagged for one year. It is striking to notice how the two series depart from each other. Clearly a substantial component of the dollar amount of investment is not driven by capacity changes. Indeed, anecdotal evidence suggests that a significant fraction of the investment in the refining industry is due to product specification changes and the adoption of pollution control equipment in response to changes in environmental regulations. In a comment about building new refineries in the U.S., Bill Greehey, the CEO of an independent refiner Valero Energy Corporation, told the press that Valero would spend $1.7 billion on meeting federal gasoline requirements in 2004 and 2005 (as reported in *San Antonio Express*, July 31, 2004). According to the Census Bureau's *Current Industrial Report*, pollution abatement capital expenditure accounts for 10-15 percent of the overall investment by the petroleum refining industry over the sample period. Investment in these mandated areas probably has little to do with the level of demand and demand uncertainty.

The micro-patterns of capacity change in percentage terms are shown in Figure 2. The underlying data represent changes in capacity between year *y* and *y+1* at the refinery level. The large spike in the middle of the distribution indicates that 74 percent of the time refineries make no change to their capacity between two adjoining years. The large number of zero investment episodes could result from either the irreversibility nature of investment or a fixed component of adjustment costs. To distinguish between the two alternatives, one must resort to more structured econometric analysis which we will turn to in section IV of the paper. In addition, a significant number (11 percent) of non-zero observations are in the interval of (-0.05, +0.05). These patterns in capacity adjustment are even "lumpier" than those reported in Cooper, Haltiwanger and Power (1999), Doms and Dunne (1998), and Nilsen and Schiantarelli (2003). For example, Nilsen and Schiantarelli report only 20 percent of their investment episodes in Norwegian manufacturing as being zero and Doms and Dunne (1998) state "…while a significant portion of investment occurs in a relatively small number of episodes, plants still invest in every period". Moreover, the additional capacity added in the industry is concentrated in a few investment episodes. Roughly 5% percent of all capacity expansion episodes (33 projects) account for 30 percent of the addition to capacity in the industry (Figure 3). These additions occur in ongoing refineries since no new refineries have been built in the US during our period of analysis. Alternatively, the large reductions in capacity observed in the data are due largely to the closure of refineries. 83 refineries close during the 1985-2003 period and these closing refineries account for 63 percent of the overall reduction of capacity observed in the data (Figure 3).

While it is plausible that a refinery may increase its capacity by a small amount through debottlenecking and incremental investment activity, it is less likely that a refinery would disinvest its capacity by a small amount. We suspect that some of the small reductions in capacities might be a result of either reporting errors or may reflect the fact that refinery engineers adjust the estimates of the capacity levels at their refinery based upon their ongoing review of the data.[9] To test the sensitivity of our results to the presence of these small adjustments in capacity, we employ two sets of alternative thresholds to measure whether a change in capacity has occurred. The first set includes three relative thresholds: a zero threshold, a 5 percent threshold, and a 10 percent threshold. For the zero threshold, any capacity change above (below) zero is defined as investment (disinvestment). For the 5 (10) percent threshold: a capacity change greater than 5 (10) percent is defined as an investment and less than -5 (-10) percent is defined as a disinvestment. The second set includes two absolute capacity change thresholds: 2500 B/SD and 5000 BS/D.[10] The investment and disinvestment using the absolute threshold values are similarly defined as the 5 (10) percent thresholds.

Theories emphasizing the role of irreversibility imply that a refiner will put off investment decisions at times of high uncertainty. To shed light on the timing of capacity adjustments, Figure 4 presents the distribution of durations between two investment/disinvestment episodes using the zero and the five percent thresholds. The duration is defined as the length (in years) of inaction period between two adjacent investment or disinvestment episodes in the same refinery.[11] For instance, if a refinery invests in both year *y* and year *y+1*, the duration is zero. If it does nothing in year *y+1* but invests in year *y* and *y+2*, the duration is one. Several points are worth making. First, consistent with the large number of zero observations in Figure 2, the majority of the durations are above zero and the median duration for the 5 percent threshold series is 3 years. Second, the fraction of refineries with very long durations between investment episodes is quite small. Third, we do see a significant number of zero duration events. This may be due to the fact

[9] We owe this point to Stephen Patterson, Survey Manager at EIA and Sidney Gale, Managing Director of EPIC Inc.
[10] While somewhat arbitrary, the 2500 B/SD and 5000 B/SD thresholds correspond to the 5% and 10% of a 50000 B/SD refinery. Following Kerr and Newell (2003), we categorize a refinery as a small refinery if its capacity is below 50000 B/SD. We also experimented other absolute thresholds, including 2000 B/SD, 3000 B/SD, 4000 B/SD, 6000 B/SD, 7000 B/SD, and the results are qualitatively similar to those reported below.
[11] Here we do not distinguish between an investment and a disinvestment.

that refinery investment episodes may span calendar years in the data. In this case, refiners would report back-to-back years of changes in capacity.

III. Measuring uncertainty

In this study, we explore an alternative approach by making use of commodity derivatives trading data. The refining process involves distillation which "cracks" crude oil into different components to make petroleum products such as gasoline and heating oil. Crude oil, gasoline and heating oil are all actively traded in the futures market in the New York Mercantile Exchange (NYMEX). Our uncertainty indicator is based on a daily forward refining margin (or crack spread, denoted as *FRM*), which is defined as

$$FRM^{d} = 2*F_{GO}^{M,d} + 1*F_{HO}^{M,d} - 3*F_{CO}^{M,d} \qquad (1)$$

where *GO, HO,* and *CO* stands for unleaded gasoline, heating oil, and crude oil respectively. $F_{(.)}^{M,d}$ denotes the price of the futures contract that is traded at day *d* and matures at month *M*.[12] The 3-2-1 refining margin reflects the gross profit from processing three barrels of crude oil into two barrels of unleaded gasoline and one barrel of heating oil. Because the 3:2:1 ratio approximates the real-world ratio of refinery output, it is commonly used in the oil industry to construct the refining margin. A recent EIA report (EIA, 2002, p. 21-22) notes that "Refinery managers are more concerned about the difference between their input and output prices than about the level of prices. Refiners' profits are tied directly to the spread, or difference, between the price of crude oil and the prices of refined products. Because refiners can reliably predict their costs other than crude oil, *the spread is their major uncertainty*."

A common interpretation of future prices describes the future prices as a forecast of the future price of commodity that incorporates a risk premium (Fama and French (1987)). In a discussion about forecasting performance of commodity futures prices, Tomek (1997) points out that although futures prices may not accurately predict future spot prices, they do as well or better

[12] The deliveries of all petroleum futures are ratable over the entire delivery month (NYMEX website).

than econometric models. Specific to the petroleum futures market, Ma (1989) compares the forecasting performance of petroleum futures (crude oil, heating oil, and leaded gasoline) markets with a variety of widely-used time-series models including random walk, ARIMA, and VAR models. She finds that, on average, forecasts based on futures markets outperform econometric models for all the three commodities. Fujihara and Mougoue (1997) provide evidence that petroleum futures prices are unbiased predictors of the future spot prices. Given these findings, we believe that the forward refining margin defined in Eq.1 should proxy market participants' expected gross margin for the industry in T based on current information.

Analogous to papers using the standard deviation of stock returns, this paper uses the annual standard deviation of the daily forward refining margin as our uncertainty indicator. The NYMEX began trading crude oil futures in March 1983, unleaded gasoline futures in December 1984, and heating oil futures in January 1980. The daily forward refining margin of (1) is calculated using daily close prices of all the three commodity contracts with 6 months time-to-maturity. The 6-month maturity is chosen because it is the longest time horizon with which we can obtain a consistent data series. The annual measures of forward refining margin (*Margin*) and the associated uncertainty measure (σ_{FRM})) are the mean and the standard deviation of daily forward margins as in (1) over a 12-month window and deflated with the implicit GDP deflator from the Bureau of Economic Analysis (BEA). Specifically,

$$Margin = \left(\sum_{d=1}^{N} FRM^{d}\right) / N \tag{1.a}$$

$$\text{and } \sigma_{FRM} = \sqrt{\frac{\sum_{d-1}^{N} (FRM^{d} - MARGIN)^2}{N-1}} \tag{1.b}$$

where N is the number of trading days in a given year.

Figure 5 plots the time series of the *Margin* and σ_{FRM}. The σ_{FRM} series appear to be heavily influenced by geopolitical events in the Middle East. The spike in 1990 is related to the first Gulf-War. Uncertainty rises again in 2003 surrounding the second Gulf War. Given the importance of

Persian Gulf in the world oil supply, it is not surprising that investors are less certain about future refining margins during periods where war threatens important supply sources.

V. Analysis of Capacity Adjustment

A. The Empirical Framework

The standard approach in the literature is to estimate a reduced form investment rate model. Given our data features episodes of capacity change interspersed with periods of inactivity, we make use of econometric techniques for survival analysis and estimate the effect of uncertainty on the timing of capacity adjustment. The survival time variable measures the time that a refinery stays in an inaction regime. Many refineries have multiple capacity change episodes during the sample period and we reset an individual refinery's clock to zero after each episode. Some refineries were in an ongoing inaction spell at the start of the sample period. For these refineries, we find out their last capacity change episode before 1985 and set the clock to zero for the first spell of each refinery.

Let T denote the length of survival time (a refinery stays in an inaction regime) with the cumulative probability distribution function $F(t)$. The probability that a refinery stays in an inaction regime longer than T is given by the survival function $S(t)=1-F(t)=Pr(T>t)$. The hazard function gives the conditional probability that a refinery change its capcaity in the interval of Δt after it stays in inaction until t. Following the notation in Kiefer (1988), the hazard function can be written as

$$\lambda(t) = \lim_{\Delta \to 0} \frac{pr(t \le T < t + \Delta t \mid T \ge t)}{\Delta t}. \tag{2}$$

Using the hazard function, the survival function $S(t)$ is written as

$$S(t) = \exp[-\Lambda(t)] = \exp[-\int_0^t \lambda(s) ds] \tag{3}$$

where $\Lambda(t) = \int_0^t \lambda(s)ds$ is the integrated hazard function.

We estimate two basic hazard models in the analysis. Our primary analysis focuses on the capacity expansion episodes in the data, similar to the focus in CHP (1999) and Nilsen and Schiantarelli (2003). In this case, we define an exit from a spell to be a capacity expansion event and treat all spells that end through capacity contraction as censored observations including refining closures. The proportional hazard model in this case is given by

$$\lambda(t, x, \beta, \lambda_0) = \exp(x'\beta)\lambda_0(t) \tag{4}$$

where λ_0 denotes the "baseline" hazard functions corresponding to zero values of the explanatory variables for the capacity expansion hazard. β is a vector of parameters to be estimated and x is a vector of explanatory variables. The effect of the *x's* on the conditional probability of ending an inactivity spell is to shift the baseline hazard proportionally (Kiefer, 1988). We also estimate a capacity adjustment hazard that defines exit from an inactivity spell as simply any capacity change – expansion or contraction.

The variables contained in x include both the *Margin* and *Uncertainty*(σ_{FRM}) variables discussed above and a number of additional variables. We control for the overall capacity utilization rate in the refining district to proxy for supply conditions in an area. [13] The variable *Urate* is the ratio of average daily input (crude) to average daily capacity. To avoid endogeneity problems, *Urate* enters equation (8) and (9) with one year's lag. We expect that if supply conditions are tight in an area this may increase (decrease) the probability of an investment (disinvestment) episode occurring. Since, Doms and Dunne (1998) find that smaller plants and plants undergoing ownership change have lumpier investment patterns, we control for these factors as well. *Ownchg* is a dummy variable that is equal to 1 within the first 2 years of ownership change and zero otherwise. *Small* is another dummy variable that is equal to 1 for

[13] A complete description and map for refining districts can be found in EIA's annual publication *Petroleum Supply Annual*.

refineries with capacity less than 50,000 B/SD and zero otherwise. To control for geographic and institutional differences across regions, a set of dummy variables for refining districts are also included in the model.

The refining industry is one of the most heavily polluting industries and is subject to a number of environmental regulations. Using plant data from the Longitudinal Research Database, Becker and Henderson (2000) find that the differential air quality regulations reduce new plant births in ozone-nonattainment areas.[14] Similarly, Greenstone (2002) finds that nonattainment counties have a lower plant-level growth rate relative to attainment counties. To control for the potential regulatory effect on the timing of refinery investments, we also make use of the data on air quality attainment status, and in particular, focus on the ozone attainment status.[15] Ozone is a major component of smog and is formed at the reaction of volatile organic compounds (VOC) and nitrogen oxides (NOx). Refining is a major source of both VOC and NOx, ranking first and second, respectively, among 18 air polluting industries (EPA, 2004). *Ozone* is a dummy variable that is equal to 1 if a refinery located in county that is nonattainment for ozone in a particular year and zero otherwise. If new investments result in an increase in the emission of a criteria pollutant, the cost of adjustment will be higher in nonattainment counties and this will lengthen the inaction period prior to an investment episode. We expect the *Ozone* variable to be negative in the investment hazard.

The recent literature on the cost of capital adjustments (CHP, 1999) suggests that positive duration dependence is consistent with non-convex forms of adjustment costs. The reason is that under the assumption of non-convex costs of adjustment (say, a fixed cost), the likelihood of net

[14] According to the Clean Air Act and its amendments, the Environmental Protection Agency (EPA) uses four criteria pollutants -- carbon monoxide (CO), ozone (O_3), sulfur dioxide (SO_2), and particulate matter – as indicator of air quality and establishes national air quality standards for each of them. A county is designated “nonattainment” if its air pollution level of a particular pollutant persistently exceeds the relevant national standards. Plants that emit a regulated pollutant in nonattainment counties are subject to stricter regulations (e.g. requiring polluters to buy a permit) than those located in attainment counties.
[15] We focus on the attainment status of ozone because it has been the most persistent air pollution problem facing the EPA and because more refineries are located in ozone nonattainment counties than the nonattainment counties of any other pollutants. However, our results that follow are robust to the inclusion of other pollutants and available from the authors upon request.

gains from a new investment being able to justify the fixed cost increases in the time since the last investment. In contrast, the best response to convex form of adjustment cost is to invest whenever there is a capital shortage. This yields positive correlation in producer-level investment series and the prediction of negative duration dependence in the hazard, though one should not observe lumpy investment. Models with irreversibility also yield positive correlations in investment and the prediction of negative duration dependence in the hazard (Bigsten, et al (2005)). The Weibull model is a natural choice for testing duration dependence. The baseline hazard for the Weibull model has the following form (the subscripts are dropped for ease of exposition):

$$\lambda_0(t) = \rho t^{\rho - 1} \tag{5}$$

When ρ=1, the Weibull model reduces to an exponential model with constant hazard. When ρ >1, the Weibull model has positive duration dependence — the hazard increases in the length of the duration. When ρ <1, the hazard has negative duration dependence.

In an attempt to account for the unobserved heterogeneity at the refinery level, we assume a multiplicative error term (frailty) v associated with each hazard specification

$$\lambda(t, x, \beta, \lambda_0) = \exp(x'\beta)\lambda_0(t)v \tag{6}$$

The frailty (v) is assumed to be gamma distributed with mean one and variance θ which is a standard assumption in this approach. Whether the unobserved heterogeneity is significant can be tested by testing whether the parameter θ is zero. When the null hypothesis is true, the model reduces to a model without frailty. We allow the frailties to be shared over the same refinery (a shared-frailty model).

Kiefer (1988, p 665) shows that equation (9) can be rewritten in the form of

$$-\rho \ln t = x'\beta + v\ . \tag{7}$$

Thus, the effect of x is to directly prolong or shorten the survival time t by a factor exp(-x'β/ρ) depending on whether the factor is greater or less than one.

B. Hazard Model Results

For the sake of robustness, we calculate three pairs of annual *Margin* and σ_{FRM} series by alternating the calculation window. The first pair (*Margin1* and $\sigma_{FRM}1$ shown in Figure 5) is simply the mean and the standard deviation of daily margins in year *y*. To allow for construction lags, we build 6- and 3- month lags in the second (*Margin2* and $\sigma_{FRM}2$) and the third pairs (*Margin3* and $\sigma_{FRM}3$), respectively. *Margin2* and $\sigma_{FRM}2$ are the mean and standard deviation of daily margins from July of year *y-1* to June of year *y*, while *Margin3* and $\sigma_{FRM}3$ are similarly defined from October of year *y-1* to September of year *y*. All margins and uncertainty measures are deflated with the implicit GDP deflator from the Bureau of Economic Analysis (BEA).

The estimation results with alternative uncertainty measures are reported in Table 2. To save space, we only present the results for the 5% relative threshold and 5000 B/SD absolute threshold as the two thresholds lead to roughly the same number of spells. The empirical results for other threshold values are qualitatively similar and are available from the authors upon request. In the capacity expansion columns, the estimated coefficients for all three uncertainty measures are negative and significant at conventional levels. Take the estimated coefficient in Panel B as an example. A 10 percent increase in $\sigma_{FRM}2$ lowers the conditional probability of ending an inaction spell with an capacity expansion episode (or increases the length of the spell) by 3.5 percent for the relative threshold and 5 percent for the absolute threshold.[16] As expected, both the *Margin* and *Urate* variables are positive in the capacity expansion hazard, although *Margin* is generally not significant and *Urate* is significant only when the investment is measured with absolute thresholds. With respect to the other variables in the capacity expansion hazard, ownership changes appear not to affect the investment hazard. The hazard is lower for smaller refineries indicating longer durations between investment episodes and this is especially true under the 5000 B/D definition. A small refiner is 39% less likely to end their inactivity spell with a 5%

[16] The model predicted the median length of an inaction spell ending with an investment episode to be 7.9 years.

increase in refining capacity than a larger refiner. *Ozone* has the expected sign although is only statistically significant under the relative threshold. A refinery in an ozone non-attainment county is 25% less likely to invest comparing with those in attainment counties.

Looking at the capacity change hazard that allows spells to end with either a positive or negative change in capacity, uncertainty still lowers the likelihood of capacity change in almost all the hazards. Most of the other variables are not statistically significant with the exception of the indicator variable on refining size. It has opposite signs in the two capacity change hazard and statistically significant. This seemingly conflicting result reflects the fact that a 5% change in capacity is a rarer event in large refineries compared to small refineries and thus smaller refineries are likely to exit a spell with a *relatively* larger capacity change. However, a 5000 B/D change is more common in large refineries.

The test of duration dependence indicates that ρ is only significantly different from 1 in the capacity change hazard (especially under the 5000 B/D definition) and only shows mildly flat upward sloping hazard. This result differs from CHP (1999) and Nilson and Schiantarelli (2003), both of which report a positive duration dependence. The technology of the refining industry allows refiners to increase capacities by small amounts through debottlenecking and it is usually more costly to build a new crude processing unit or a new refinery. Thus, both the technological and econometric evidence suggest some elements of capacity change may be consistent with the presence of convex adjustment costs. One possibility is that refiners making debottlenecking type adjustments may incur convex type costs while the addition of entire cracking units may require the refiner to bear significant fixed adjustment costs. The presence of a mix of fixed and convex adjustments costs is explored in Cooper and Haltiwanger (2006). Finally, the log likelihood ratio test for frailty suggests that there is a statistically significant level of unobserved heterogeneity and the frailty model specification is necessary.

To check whether the results are sensitive to our threshold definition of capacity adjustment, we report a set of results using alternative adjustment thresholds in Table 3. The top panel uses the zero threshold definition and this definition simply makes use of the raw changes in capacity to measure investment episodes. Recall the 5% (10%) and 2500 B/SD (5000 B/SD) thresholds require a change of 5% (10%) and 2500 B/SD (5000 B/SD) or more, respectively, to trigger an investment/disinvestment episode. All three panels in Table 3 are consistent with the findings in Table 2. The uncertainty measure is negative and statistically significant in the both the capacity expansion and capacity change hazards across all thresholds. The magnitude of the effect is somewhat greater however as the threshold increases. A 10% increase in uncertainty decreases the hazard rate by 3% under the zero threshold and by 4.2% under the 10% threshold. Moreover, the results for the other variables in the model appear to have the same pattern across the alternative thresholds with the exception of size. The effect of size is again sensitive to the definition of thresholds and the definition of the spell (capacity expansion or capacity change). As the %-based threshold increases, the coefficient on the *Small* variable increases. Note, however, that this is not the case under the absolute threshold definition.

Table 4 present the results of a model where we replace the refining margin measure of uncertainty with a stock market index based measure of uncertainty. We construct an uncertainty measure (σ_{OI}) from a stock market index that is designed to measure the financial performance of publicly traded oil companies. The oil index (symbol: XOI) is comprised of 13 major oil companies (including independent refiners) and is traded at the American Stock Exchange (AMEX). σ_{OI} is the annual standard deviation of the daily return of this oil index. Again, the results are clear. Across alternative thresholds, there is no statistically significant effect of stock market uncertainty on the capacity expansion decision.

The last exercise we perform presents some alternative specifications for our empirical model. We present an accelerated failure time (AFT) model that allows for a nonmontonic baseline hazard – the lognormal and a partial likelihood Cox (1975) model that does not assume any functional form for the baseline hazard model. The Weibull model presented throughout the analysis allows for increasing or decreasing hazards, however, it assumes the baseline hazard $\lambda_0(t)$ function is monotonically increasing or decreasing in time. In contrast, the baseline hazard function of the lognormal models first increases then decreases in time.[17] The Cox model is estimated to see if our results are sensitive to the parameterization of the baseline hazards. The advantage of the parametric forms is that they are more efficient then the Cox proportional hazard model if the assumptions regarding the parameterization of the baseline hazard are correct (Favero et al, 1994).

Table 5 presents the results for the investment hazard of these alternative specifications. The coefficients in the lognormal models are interpreted quite differently from the proportional hazard models (Weibull and Cox). A positive coefficient in the lognormal model means that time to failure is delayed while a negative coefficient means that time to failure is accelerated. The results from both the lognormal and the Cox models are quite similar and consistent with the Weibull model (presented in column (1) and (3) of the table). In the lognormal model, an increase in the uncertainty of the refining margin delays the ending of a spell while an increase in the margin and the capacity utilization rate accelerates the ending of a spell. The shape parameter indicates the baseline hazard increases for the first 3-4 years after a capacity expansion episode and then decreases. In the next subsection, we turn to a more flexible discrete hazard specification to further examine the duration dependence. The estimated coefficients from the Cox model are fairly close to the Weibull model. The results are consistent across all investment thresholds.

C. Discrete Hazard Models(INCOMPLETE)

In the above analysis, we have employed continuous hazard specifications. To check whether our results are sensitive to the continuous time assumption, we present a model of

[17] Both the lognormal and the log-logistic models allow for a non-monotonic baseline hazard function. Although not reported, the empirical results from the log-logistic model are similar to those of the lognormal models in Table 5. The lognormal models yield a higher log likelihood values.

discrete hazard model that is similar to CHP (1999) and Nilsen and Schiantarelli (2003) in this subsection. Following Jenkins (1995) and CHP, we parameterize the hazard as

$$\lambda(t,x,\beta)=1-\exp(-\exp(\varphi+\sum_{s=2}^{S}\gamma_s D_{siy}+x_{iy}'\beta)) \tag{8}$$

where D_{siy} is a set of duration dummies, equal to 1 if year y is the sth year from the last investment episode.[18] S denotes the longest spell duration. x_{iy} is a vector of explanatory variables as defined in section IV.A. φ is the intercept, γ*'s* and β*'s* are the coefficients to be estimated. From the estimated γ's, one can construct a non-parametric estimation of the baseline hazard.

To control for the unobserved heterogeneity, we have also applied Heckman and Singer's (1984) approach by allowing the intercept term φ in the hazard function (8) to differ. We model the distribution of the φ by a discrete distribution of Z mass points. Each mass point has probability α_z. The hazard function for a spell belonging to type z is:

$$\lambda_z(t,x,\beta)=1-\exp(-\exp(\varphi_z+\sum_{s=2}^{S}\gamma_s D_{siy}+x_{iy}'\beta)) \tag{9}$$

The maximum likelihood estimation produces estimates of the parameters φ_z*'s,* β_z's, and γ_s's, as well as the estimated probabilities (α_z's).

Table 6 reports the results from estimating (11) and (12) with zero, 5%, and 2500 B/SD thresholds. The results from using 10%, 5000 B/SD thresholds are not materially different and therefore omitted for brevity's sake. In estimating (12), we have set the number of mass points Z = 2 (φ_1 is normalized to zero). The results are virtually the same if we set Z = 3. The estimated α's indicate that 80-90% of the spells belong to Group 1. The signs of the estimated coefficients for *Margin,* σ_{FRM}*,* *Urate*, and *Small* are all consistent with Table 2-4. In particular, the uncertainty measure σ_{FRM} is negative and significant in five out of the six model specifications and thresholds,

[18] For example, if an investment episode occurs in year t, then s is equal to 1 in year t+1.

indicating that our finding of a negative relationship between uncertainty and investment in previous sections is not sensitive to the choice of continuous hazard models.

Figure 6 depicts the shape of the baseline hazards implied by the estimated coefficients of the duration dummies in Table 6. The figures in 6_a, 6_c, and 6_e present the baseline hazard functions for the no-frailty case. The hazard function is downward sloping for the first three years (up to D2) following an investment episode, and remains relatively flat after the third year. However, once the unobserved heterogeneity is controlled for, the hazard rates in the first three years are not significantly different from the latter years. The increasing hazard in CHP (1999) and the U-shape pattern in Nilsen and Schiantarelli (2003) do not appear in our data.

V. Conclusion

There are two main contributions of the paper. First, the paper uses forward measures from financial markets on commodities to construct estimates of market uncertainty. These measures of commodity price uncertainty reflect uncertainties in both input and output prices faced by the refiner. Refiners' decisions to make investments are clearly related to these measures of uncertainty. As uncertainty rises, refiners delay their investment decisions. This finding agrees with a number of papers that emphasize the option-value of waiting to invest. Second, we use data on changes in the actual capacity of refiners to measure investment episodes. We believe that these data offer a cleaner assessment of the capital stock changes of producers than those based on accounting type data. We also show that our results are very robust to investment thresholds used in the analysis and model specifications.

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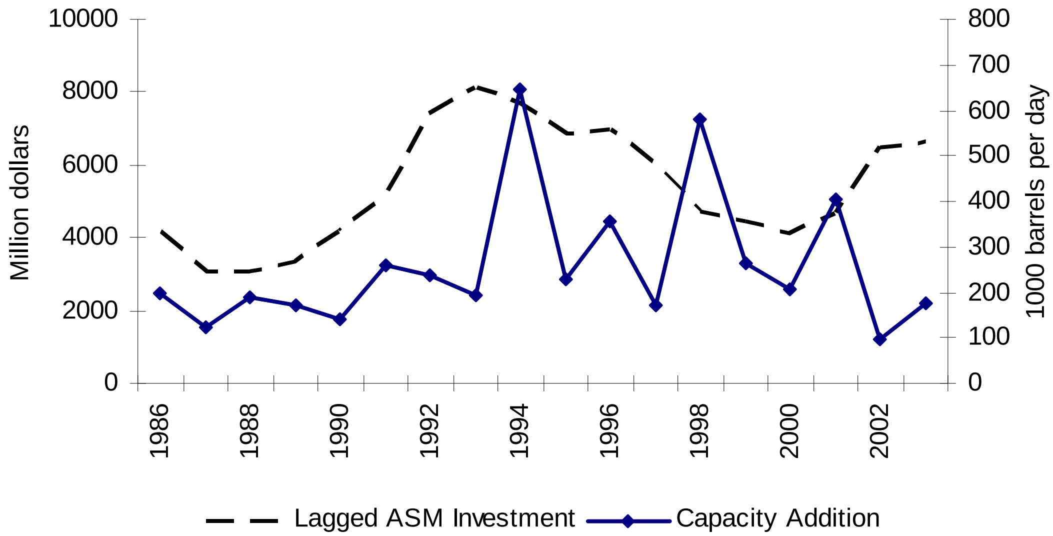
Figure 1

Aggregate Investment and Capacity Addition

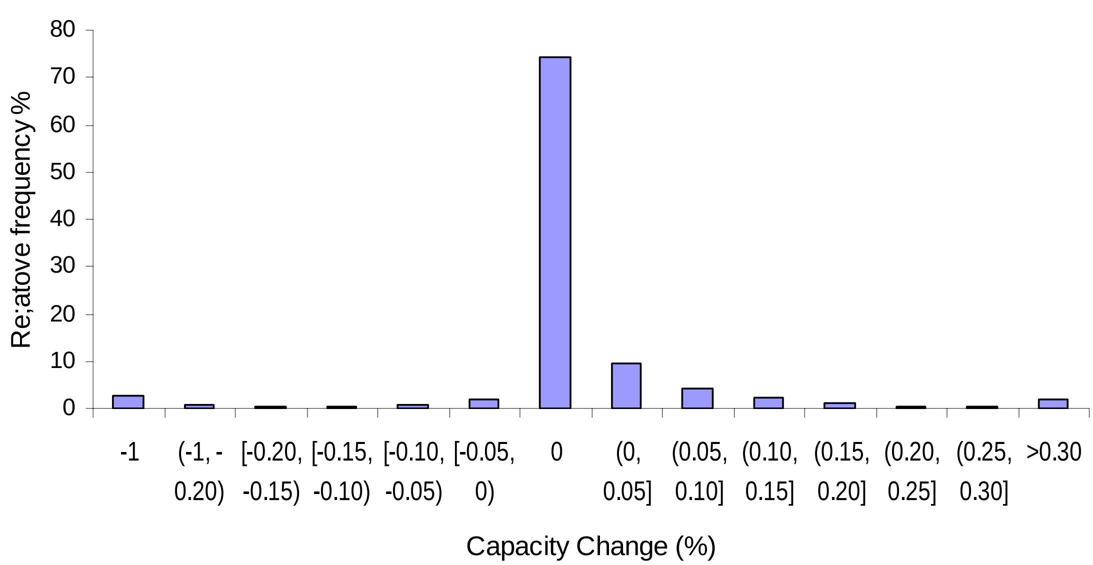


Data Source:

(1) Capacity addition is from Petroleum Supply Annual of EIA, various issues.
(2) ASM 1985-1996 investment is from NBER "Manufacturing Industry Productivity Database" collected by Bartelsman, Becker, Gray. 1997-2003 data is from the Annual Survey of Manufacturers, Census Bureau and is deflated the price index of private nonresidential structures investment in the Economic Report to the President.

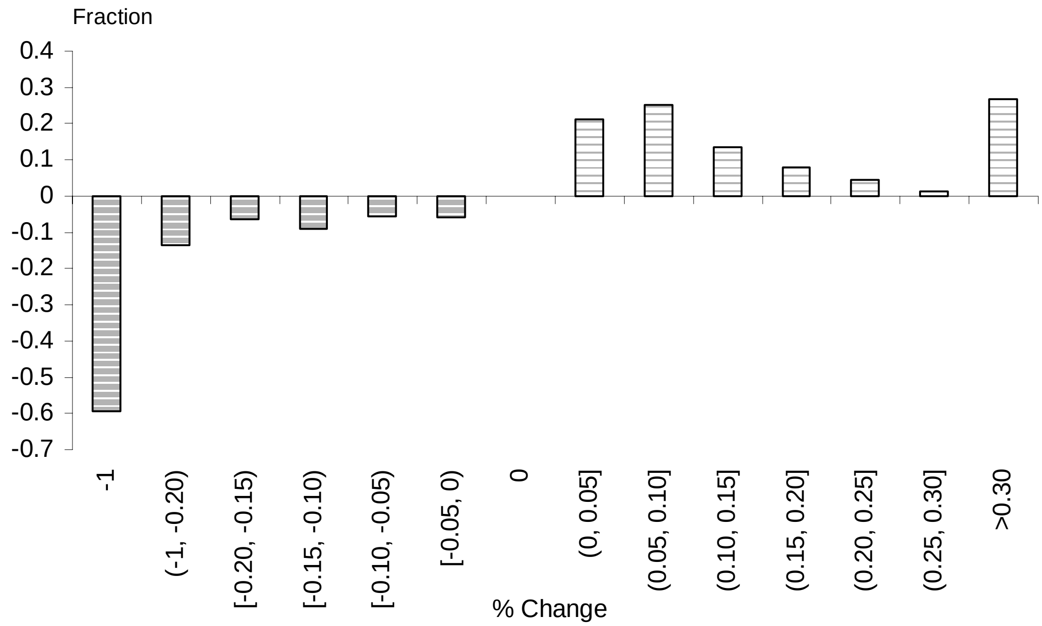
Figure 2

Refinery Capacity Change Distribution



Total number of observations: 3324.
The far left bar (-1) represents complete shut-down refineries.

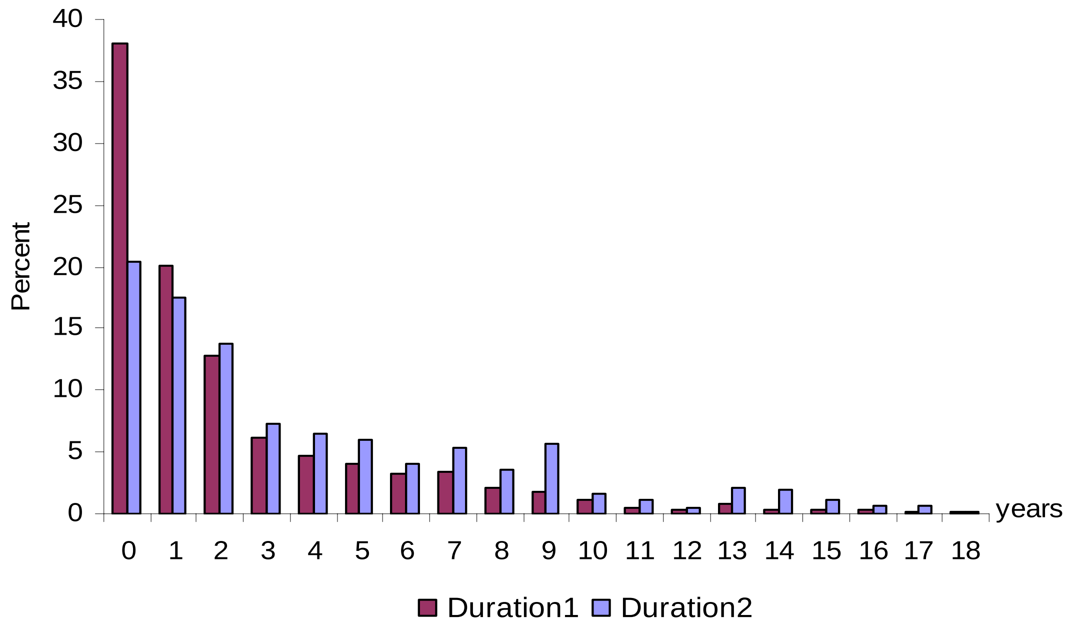
Figure 3



Note: Each positive bar represents the fraction of total investment associated with each relative category (e.g. 5-10%). Likewise, each negative bar represents the fraction of disinvestment associated with each relative category

Figure 4

Distribution of Durations between Two Capacity Change Episodes



Notes
Duration 1: Years of duration between two capacity change episodes with zero threshold.
Duration2: Years of duration between two capacity change episodes with 5% threshold.

Figure 5

Forward Refining Margin and Uncertainty Measure

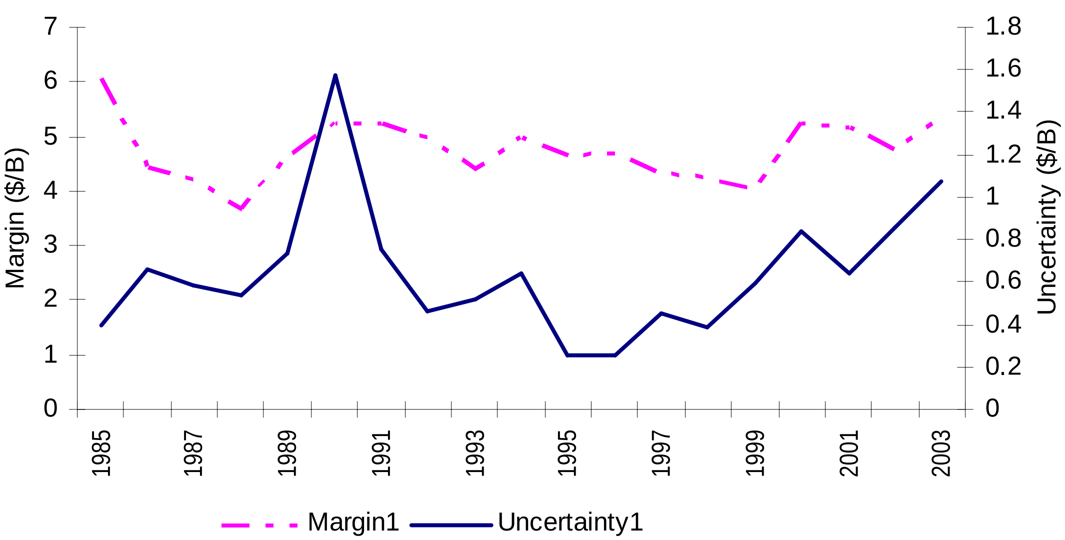


Figure 6_a

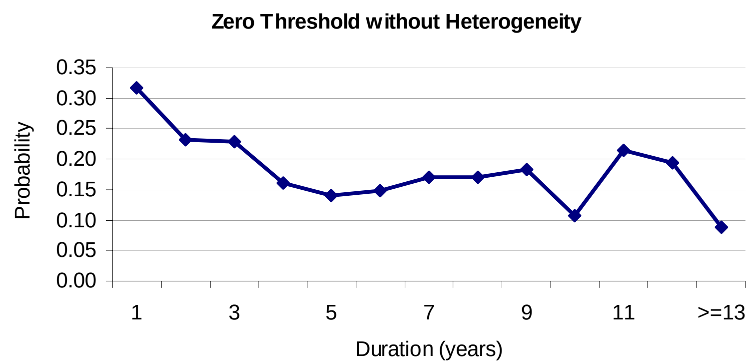


Figure 6_b

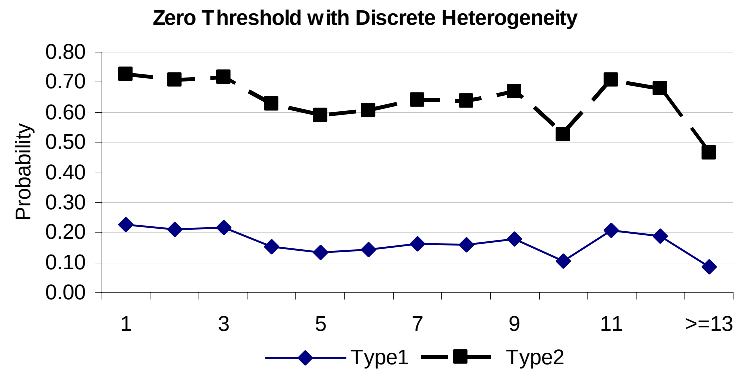


Figure 6_c

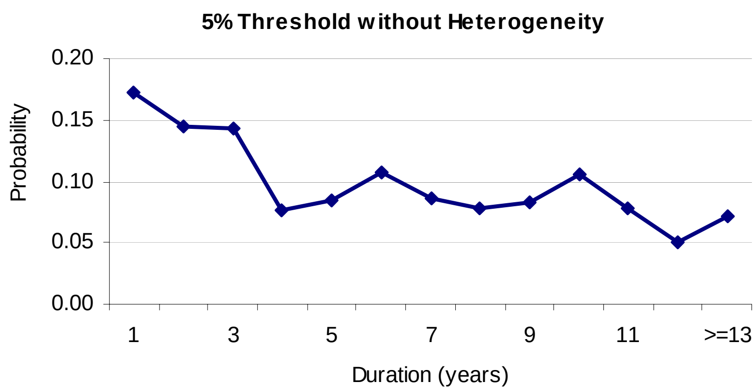


Figure 6_d

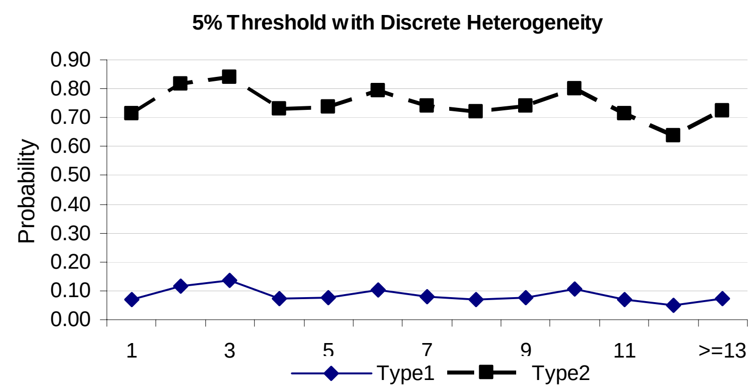


Figure 6_e

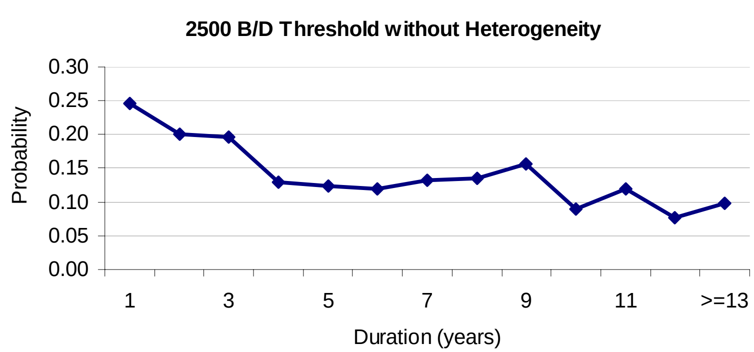


Figure 6_f

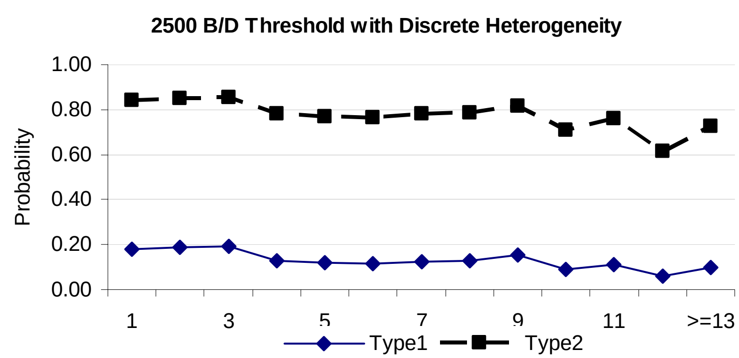


Table 1. Summary Statistics

	Mean	Std. Deviation	Minimum	Maximum
Urate1 (%)	86.98	7.66	60.71	102.80
Margin1 ($/B)	4.75	0.57	3.66	6.03
Margin2 ($/B)	4.72	0.64	3.57	6.05
Margin3 ($/B)	4.72	0.58	3.48	5.96
$\sigma_{FRM}1$, ($/B)	0.64	0.30	0.25	1.57
$\sigma_{FRM}2$, ($/B)	0.59	0.24	0.22	1.24
$\sigma_{FRM}3$ ($/B)	0.62	0.24	0.21	1.15
σ_{OI} (%)	1.15	0.39	0.62	2.14

Table 2. Estimation Results with Alternative Uncertainty Measures
(5% and 5000 B/D Thresholds)

	Capacity Expansion		Overall Capacity Change	
	5% Threshold	5000 B/D Threshold	5% Threshold	5000 B/D Threshold
Panel A				
Margin1	0.096	0.092	-0.044	-0.048
	(0.104)	(0.113)	(0.083)	(0.089)
$\sigma_{FRM}1$	-0.377*	-0.584***	-0.383**	-0.507***
	(0.205)	(0.220)	(0.175)	(0.183)
Urate	-0.001	0.022**	-0.009	0.010
	(0.009)	(0.010)	(0.008)	(0.008)
Ownchg	-0.001	-0.020	0.017	-0.130
	(0.204)	(0.198)	(0.173)	(0.177)
Small	-0.488***	-2.019***	0.226*	-0.501***
	(0.148)	(0.233)	(0.122)	(0.159)
Ozone	-0.298**	-0.220	-0.190	-0.165
	(.147)	(0.168)	(0.123)	(0.142)
ρ (H_0: ρ=1)	1.040	1.085	1.090	1.132**
	(0.059)	(0.056)	(0.053)	(0.051)
LR test (H_0: θ=0), χ^2	5.10**	17.39***	6.61***	28.69***
No of spells	600	586	600	586
Log likelihood	-614.93	-569.99	-688.46	-677.84
Panel B				
Margin2	0.147	0.188*	0.055	0.096
	(0.101)	(0.109)	(0.081)	(0.086)
$\sigma_{FRM}2$	-0.579**	-0.838***	-0.488**	-0.601***
	(0.266)	(0.281)	(0.221)	(0.227)
Urate	0.001	0.023**	-0.008	0.013
	(0.010)	(0.010)	(0.008)	(0.008)
Ownchg	-0.016	-0.045	0.008	-0.144
	(0.204)	(0.198)	(0.173)	(0.177)
Small	-0.487***	-2.014***	0.234*	-0.485***
	(0.148)	(0.233)	(0.122)	(0.160)
Ozone	-0.288*	-0.199	-0.182	-0.153
	(0.147)	(0.168)	(0.123)	(0.142)
ρ (H_0: ρ=1)	1.042	1.088	1.089	1.134**
	(0.059)	(0.057)	(0.053)	(0.051)
LR test (H_0: θ=0): χ^2	5.25**	17.44***	6.76***	29.04***
No. of spells	600	586	600	586
Log likelihood	-614.15	-569.01	-689.08	-679.35
Panel C				
Margin3	0.132	0.159	0.009	0.036
	(0.105)	(0.114)	(0.084)	(0.090)
$\sigma_{FRM}3$	-0.413*	-0.647**	-0.333	-0.462**
	(0.251)	(0.268)	(0.207)	(0.217)
Urate	0.001	0.021**	-0.009	-0.010
	(0.009)	(0.010)	(0.008)	(0.008)
Ownchg	-0.009	-0.033	0.009	-0.138
	(0.204)	(0.198)	(0.173)	(0.177)
Small	-0.482***	-2.005***	0.236*	-0.482***
	(0.147)	(0.232)	(0.122)	(0.160)
Ozone	-0.291**	-0.206	-0.184	-0.158
	(0.147)	(0.167)	(0.123)	(0.143)
ρ (H_0: ρ=1)	1.041	1.084	1.089**	1.132**
	(0.059)	(0.057)	(0.053)	(0.051)
LR test (H_0: θ=0), χ^2	5.01**	17.05***	6.42***	28.81***
No. of spells	600	586	600	586
Log likelihood	-615.13	570.64	-690.21	-380.57

Notes: (1) Regional dummies are included but not reported. (2) Standard errors are reported in parenthesis. (3) *** (**, *) denotes significance at the 1 (5, 10) percent level.

Table 3. Estimation Result with Different Threshold Values of Investment

	Capacity Expansion		Capacity Change	
	Zero threshold		**Zero threshold**	
Margin2	0.078		0.036	
	(0.076)		(0.064)	
$\sigma_{FRM}2$	-0.499***		-0.364**	
	(0.194)		(0.165)	
Urate	0.022***		0.014**	
	(0.007)		(0.006)	
Ownchg	0.146		0.148	
	(0.136)		(0.120)	
Small	-1.024***		-0.423***	
	(-0.128)		(0.108)	
Ozone	-0.248**		-0.194*	
	(0.118)		(0.103)	
ρ (H_0: ρ=1)	1.151***		1.185***	
	(0.039)		(0.036)	
LR test (H_0: θ=0), χ^2	25.02***		30.14***	
No. of spells	957		957	
Log likelihood	-1045.88		-1132.14	
	5% threshold	**2500 B/D threshold**	**5% threshold**	**2500 B/D threshold**
Margin2	0.147	0.215**	0.055	0.119
	(0.101)	(0.092)	(0.081)	(0.075)
$\sigma_{FRM}2$	-0.579**	-0.766***	-0.488**	-0.546***
	(0.266)	(0.233)	(0.221)	(0.196)
Urate	0.001	0.027***	-0.008	0.015**
	(0.010)	(0.009)	(0.008)	(0.007)
Ownchg	-0.016	-0.055	0.008	-0.059
	(0.204)	(0.171)	(0.173)	(0.152)
Small	-0.487***	-1.510***	0.234*	-0.545***
	(0.148)	(0.169)	(0.122)	(0.135)
Ozone	-0.288*	-0.092	-0.182	0.076
	(0.147)	(0.137)	(0.123)	(0.122)
ρ (H_0: ρ=1)	1.042	1.136***	1.089	1.170***
	(0.059)	(0.048)	(0.053)	(0.044)
LR test (H_0: θ=0), χ^2	5.25***	19.33***	6.72***	30.81***
No. of spells	600	724	600	724
Log likelihood	-614.15	-745.29	-689.08	-839.55
	10% threshold	**5000 B/D threshold**	**10% threshold**	**5000 B/D threshold**
Margin2	0.250*	0.188*	0.064	0.096
	(0.130)	(0.109)	(0.097)	(0.086)
$\sigma_{FRM}2$	-0.726**	-0.838***	-0.526*	-0.601***
	(0.353)	(0.281)	(0.273)	(0.227)
Urate	-0.011	0.023**	-0.013	0.013
	(0.013)	(0.010)	(0.010)	(0.008)
Ownchg	-0.070	-0.045	-0.011	-0.144
	(0.265)	(0.198)	(0.217)	(0.177)
Small	0.112	-2.014***	0.821***	-0.485***
	(0.202)	(0.233)	(0.158)	(0.160)
Ozone	-0.357*	-0.199	0.190	-0.153
	(0.205)	(0.168)	(0.154)	(0.142)
ρ (H_0: ρ=1)	0.995	1.088	1.028	1.134**
	(0.082)	(0.057)	(0.070)	(0.051)
LR test (H_0: θ=0), χ^2	8.40***	17.44***	5.46***	29.04***
No. of spells	444	586	444	586
Log likelihood	-400.66	-569.01	-484.96	-679.35

Notes: (1) Regional dummies are included but not reported. (2) Standard errors are reported in parenthesis. (3) *** (**, *) denotes significance at the 1 (5, 10) percent level.

Table 4. Investment Hazard Using Stock Price Volatilities

	Relative Thresholds		Absolute Thresholds	
	Margin ($\sigma_{FRM}2$)	Stock Index (σ_{OI})	Margin ($\sigma_{FRM}2$)	Stock Index (σ_{OI})
	Zero Threshold (957 Spells)			
Margin2	0.082 (0.076)	0.015 (0.072)		
Uncertainty	-0.514*** (0.194)	0.108 (0.111)		
Urate	0.025*** (0.007)	0.027*** (0.007)		
ρ (H_0: ρ=1)	1.151*** (0.039)	1.154*** (0.039)		
Log Likelihood	-1048.10	-1051.24		
	5% Threshold (600 Spells)		**2500 B/D Threshold (724)**	
Margin2	0.150 (0.101)	0.028 (0.099)	0.216** (0.092)	0.071 (0.086)
Uncertainty	-0.596** (0.266)	-0.149 (0.161)	-0.772*** (0.233)	-0.064 (0.136)
Urate	0.004 (0.010)	0.002 (0.010)	0.029*** (0.009)	0.029*** (0.009)
ρ (H_0: ρ=1)	1.044 (0.059)	1.040 (0.059)	1.136*** (0.048)	1.131*** (0.048)
Log Likelihood	-616.04	-618.18	-745.51	-751.08
	10% Threshold (444 Spells)		**500 B/D Threshold (586)**	
Margin2	0.254* (0.130)	0.148 (0.129)	0.193* (0.109)	0.018 (0.104)
Uncertainty	-0.745** (0.353)	-0.009 (0.217)	-0.852*** (0.281)	-0.168 (0.162)
Urate	-0.007 (0.012)	-0.009 (0.013)	0.026** (0.010)	0.026** (0.010)
ρ (H_0: ρ=1)	1.007 (0.082)	0.991 (0.082)	1.088 (0.057)	1.081 (0.056)
Log Likelihood	-402.17	-404.50	-569.72	-573.95

Notes: (1) Standard errors are in parenthesis. (2) *** (**, *) denotes significance at the 1 (5, 10) percent level.

Table 5. Investment Hazard Result with Alternative Specifications

	Relative Thresholds			Absolute Thresholds		
	Weibull	Log Normal	Cox	Weibull	Log Normal	Cox
	Zero Threshold (957 Spells)					
Margin2	0.082	-0.056	0.084			
	(0.076)	(.064)	(0.060)			
$\sigma_{FRM}2$	-0.514***	0.453***	-0.527***			
	(0.194)	(0.167)	(0.154)			
Urate	0.025***	-0.019***	0.019***			
	(0.007)	(0.006)	(0.007)			
Shape Parameters	1.151***	0.922***				
	(0.039)	(0.030)				
Log Likelihood	-1048.10	-970.83	-3725.74			
	5% Threshold (600 Spells)			**2500 B/D Threshold (724 Spells)**		
Margin2	0.150	-0.165	0.151*	0.216**	-0.205**	0.218***
	(0.101)	(0.107)	(0.084)	(0.092)	(0.083)	(0.072)
$\sigma_{FRM}2$	-0.596**	0.611**	-0.546**	-0.772***	0.748***	-0.693***
	(0.266)	(0.283)	(0.222)	(0.233)	(0.215)	(0.186)
Urate	0.004	-0.004	0.005	0.029***	-0.016**	0.020**
	(0.010)	(0.010)	(0.010)	(0.009)	(0.008)	(0.009)
Shape Parameters	1.044	1.184***		1.136***	0.995***	
	(0.059)	(0.054)		(0.048)	(0.038)	
Log Likelihood	-616.04	-595.70	-1710.28	-745.51	-708.90	-2406.20
	10% Threshold (444 Spells)			**5000 B/D Threshold (586 Spells)**		
Margin2	0.254*	-0.317**	0.225*	0.193*	-0.183*	0.203**
	(0.130)	(0.153)	(0.122)	(0.109)	(0.107)	(0.099)
$\sigma_{FRM}2$	-0.745**	0.817**	-0.666**	-0.852***	0.969***	-0.788***
	(0.353)	(0.419)	(0.311)	(0.281)	(0.281)	(0.250)
Urate	-0.007	-0.003	0.005	0.026**	-0.013	0.018*
	(0.012)	(0.115)	(0.013)	(0.010)	(0.010)	(0.011)
Shape Parameters	1.007	1.396***		1.088	1.115**	
	(0.082)	(0.092)		(0.057)	(0.051)	
Log Likelihood	-402.17	-392.72	-900.18	-569.72	-554.25	-1623.43

Notes: (1) Standard errors are in parenthesis. (2) *** (**, *) denotes significance at the 1 (5, 10) percent level.
(3) The significance levels of ancillary parameters (ρ, δ, γ) are based on logarithm transformations. (4) The Cox model reports partial log-likelihood values.

Table 6. Discrete Investment Hazard Estimation Results

	Zero Threshold		5% Threshold		2500 B/D Threshold	
	Logit	Mass Point Logit	Logit	Mass Point Logit	Logit	Mass Point Logit
Margin2	0.084 (0.075)	0.013 (0.095)	0.160 (0.101)	0.036 (0.137)	0.243*** (0.091)	0.165 (0.112)
$\sigma_{FRM}2$	-0.618*** (0.198)	-0.482** (0.243)	-0.590** (0.267)	-0.306 (0.342)	-0.825*** (0.237)	-0.663** (0.278)
Urate	0.022*** (0.007)	0.036*** (0.011)	0.004 (0.009)	0.027* (0.016)	0.023*** (0.009)	0.037*** (0.013)
Small	-0.818*** (0.104)	-1.006*** (0.157)	-0.430*** (0.130)	-0.581*** (0.175)	-1.260*** (0.148)	-1.530*** (0.217)
Ozone	-0.153* (0.094)	-0.178 (0.112)	-0.272** (0.131)	-0.304* (0.171)	-0.081 (0.112)	-0.111 (0.131)
D2	-0.429*** (0.117)	-0.098 (0.206)	-0.201 (0.189)	0.465 (0.415)	-0.267* (0.143)	0.069 (0.253)
D3	-0.441*** (0.134)	-0.052 (0.245)	-0.217 (0.199)	0.753 (0.626)	-0.289* (0.160)	0.099 (0.279)
D4	-0.882*** (0.179)	-0.466 (0.287)	-0.906*** (0.265)	0.079 (0.658)	-0.791*** (0.214)	-0.388 (0.320)
D5	-1.038*** (0.207)	-0.626** (0.314)	-0.796*** (0.259)	0.124 (0.637)	-0.838*** (0.236)	-0.468 (0.337)
D6	-0.981*** (0.220)	-0.563* (0.327)	-0.543** (0.249)	0.437 (0.649)	-0.876*** (0.259)	-0.474 (0.363)
D7	-0.811*** (0.224)	-0.414 (0.328)	-0.776*** (0.293)	0.141 (0.658)	-0.761*** (0.274)	-0.392 (0.372)
D8	-0.815*** (0.245)	-0.426 (0.339)	-0.886*** (0.325)	0.035 (0.679)	-0.731** (0.292)	-0.366 (0.382)
D9	-0.724*** (0.252)	-0.300 (0.352)	-0.809** (0.325)	0.134 (0.691)	-0.571** (0.283)	-0.167 (0.375)
D10	-1.354*** (0.385)	-0.898* (0.462)	-0.532** (0.313)	0.462 (0.698)	-1.196*** (0.419)	-0.777 (0.486)
D11	-0.526* (0.277)	-0.118 (0.376)	-0.876** (0.374)	-0.005 (0.702)	-0.886** (0.367)	-0.521 (0.452)
D12	-0.654** (0.326)	-0.251 (0.418)	-1.339*** (0.464)	-0.349 (0.775)	-1.370*** (0.458)	-1.200** (0.549)
D13 & above	-1.557*** (0.222)	-1.132*** (0.335)	-0.970*** (0.194)	0.044 (0.652)	-1.092*** (0.184)	-0.670 (0.300)
Constant 1	2.410*** (0.775)	-3.828*** (1.216)	-2.030* (1.081)	-4.499** (1.841)	-3.478*** (0.979)	-4.817*** (1.336)
Constant 2		2.296*** (0.513)		3.231*** (0.572)		3.200*** (0.623)
α_1		0.838 (0.854)		0.861 (0.699)		0.897 (1.059)
α_2		0.162** (0.084)		0.139 (0.053)		0.103** (0.051)
Log L	-1458.54	-1455.92	-1014.59	-1012.12	-1140.82	-1137.93